Understanding the drivers of customers' continuance intention to use AI chatbots in e-commerce

🆔 *Huy Quang Tran* [a]*

[a] *Postgraduate Program in Management, I-Shou University, No.1, Section 1, Syuecheng Rd., Dashu District, Kaohsiung 84001, Taiwan*

ABSTRACT

The e-commerce experience has been transformed by artificial intelligence, which has also opened new avenues for customer communication through chatbots. This study aims to examine how chatbot characteristics influence continuance intention in e-commerce. Specifically, it explores how interactivity, compatibility, information quality, and service quality affect users' perceptions of chatbot usefulness and enjoyment. A quantitative approach using Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed for data analysis. The main findings reveal that (i) information quality and service quality positively influence both perceived usefulness and perceived enjoyment of chatbots, which in turn enhance continuance intention; (ii) compatibility positively affects perceived enjoyment but not perceived usefulness; and (iii) interactivity moderates the relationship between information quality and both perceived usefulness and enjoyment. This study extends the Technology Acceptance Model by incorporating service-related and interactive factors, contributing to the growing body of knowledge on consumer behavior and technology adoption in e-commerce. The findings offer valuable insights for chatbot designers, managers, and customer service practitioners.

Introduction

Due to the rising number of e-consumers and the rapid changes occurring within various industries, e-commerce is under pressure to stand out in an increasingly digital world by providing a greater customer experience (Letheren et al., 2020). Artificial intelligence (AI) is now responsible for 26% of all customer support contacts globally as of 2024, up more than 700% from 2017 (Bharatkumar, 2024). Chatbots powered by AI are more advanced, capable, and powerful than the older iterations of chatbots, which were basic answer platforms, expanding the human-technology connection (Setälä et al., 2025). Through the use of technology-mediated learning, they improve frontline experiences in service interactions by strengthening and replacing frontline employees (Lu et al., 2019). Retail chatbots, for instance, provide entertaining methods to purchase using an engaging conversational interface, inviting them to browse, informing them about things, and making frequent upselling attempts with their purchases (Przegalinska et al., 2019). In the e-retailing service industry, chatbots frequently provide a search or decision support role, offering quick, innovative, interactive, and engaging customer care interactions.

Despite the fact that earlier studies have attempted to investigate chatbots' role and importance in customer support interactions (Hari et al., 2022), very few studies look at what factors help chatbots interact with customers more effectively and efficiently. Research on chatbots is limited, and much of it has come from the viewpoint of company management, ignoring customer-centric aspects of chatbot usefulness (Lu et al., 2019). 85% of e-commerce businesses have established an intention to install chatbot to provide automated customer dialogue (Gartner, 2018). Therefore, it is reasonable to say there is a call for a deeper understanding of the attitudes and actions of customers about chatbots in the context of e-shopping, taking into account the impact of the chatbots' unique characteristics.

The Technology Acceptance Model by Davis (1989) identifies Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) as core predictors of adoption of technology, but its utilitarian assumptions limit its relevance in complex, service-oriented contexts like AI-driven chatbots. To address this, we extend TAM by incorporating five additional factors – Interactivity (INT), information quality (IQ), service quality (SQ), perceived enjoyment (PE), and compatibility (COM) - that better capture the experience-driven nature of chatbot use in e-commerce.

This research offers a conceptual model with the aim of identifying the major antecedents of PU and PE in chatbot interaction and their impact on continuance intention (CI) in the context of e-commerce. To clarify how quality-driven and experiential aspects influence customer reactions to AI-powered service agents, this study extends the TAM and incorporates compatibility, information quality, service quality, and interaction into this framework. Furthermore, it aims to investigate the factors influencing consumers' CI to use chatbots in e-commerce.

Literature Review

Theoretical and Conceptual Background

Technology Acceptance Model

In the field of information systems research, the TAM is a well-known theoretical framework that aims to understand how individuals adopt technology. In the TAM application of the Theory of Reasoned Action (TRA), Davis (1989) concentrated on two primary aspects: PU and PEOU. PEOU refers to how easy a technology is to use, while PU refers to how much people believe it will increase their performance and productivity. These two factors, as highlighted by the TAM, are the main factors that influence consumers' intentions to accept and utilise a technology.

TAM has been used in a variety of settings to study how people accept and utilise various technologies, including social networking, mobile apps, and e-commerce. It has been used to forecast and clarify users' attitudes and behaviour towards its adoption and usage. With the introduction of variants like the TAM2, this model has been significantly improved throughout time. In their 2008 contribution to the TAM, Venkatesh and Bala admit that PU and PE have a big impact on end-user adoption. The TAM and its addition version by Venkatesh and Bala (2008) serve as the foundation for this investigation.

AI Chatbot in E-commerce

An AI chatbot is a software application designed to imitate human conversation by leveraging AI and natural language processing capabilities. AI chatbots may innovate for both small business owners and large businesses thanks to technical improvements; they are no longer an expensive, inaccessible tool. In e-commerce, AI chatbots have offered several distinct commercial advantages. AI chatbots may first comprehend consumer demands and automate customer service in order to effectively respond to their needs (Letheren et al., 2020). Additionally, AI-enabled chatbots are consistently able to build positive relationships with clients since they do not suffer from bad emotions or work fatigue as people do (Przegalinska et al., 2019). AI chatbots may be used for a number of online tasks, such as customer service, site guides, virtual assistants, and sales representatives. It has been recognised that chatbots are crucial for increasing engagement since they are conversational, data-driven, and predictive. It has been demonstrated that chatbots improve the online customer experience by giving users the impression that they are getting help when they need it (Hari et al. (2022).

Compatibility

In one of the first conceptualisations of compatibility (COM), Rogers (1995) defined it as the amount to which adopting innovation is compatible with sociocultural attitudes and values, prospective adopters' desires, and past and current experiences. In their expanded view of COM, Tornatzky and Klein (1982) propose two types: normative or cognitive COM, which aligns with individuals' perception of practical, innovation, or operational COM, which aligns with their actual behaviours and practices. This research uses Roger (1995)'s definition of COM as the integration of technology with user demands, experience, and values.

More COM increases a technology's likelihood of adoption (Setälä et al., 2025). A compatible chatbot understands and answers users' questions and gives relevant information and solutions. The chatbot's usefulness increases because it satisfies users' wants and helps them reach their goals.

Hypothesis 1 (H1): COM positively affects the PU of chatbot users.

Hypothesis 2 (H2): COM positively affects the PE of chatbot users.

Information quality

Information quality (IQ), as stated by Setia et al. (2013), refers to the precision, structure, exhaustiveness, and reliability of data generated by a technological approach. A system's efficacy could be heavily influenced by the quality of its information, according to previous research (Chen & Tsai, 2019). Valid, up-to-date information is more likely to make users happy (Veeramootoo et al., 2018). It is crucial that the information be well-structured, understandable, reliable, and helpful when it comes to chatbots because these technologies are often made to help clients locate important information and give assistance, instruction, and recommendations.

According to research by Merkouris et al. (2022), a chatbot's IQ serves as a predictor of a satisfying user experience. Customers who receive accurate, timely, and pertinent information from chatbots are more likely to be satisfied and think that purchasing is more fun and beneficial.

Hypothesis 3 (H3): IQ positively affects the PU of chatbot users.

Hypothesis 4 (H4): IQ positively affects the PE of chatbot users.

Service quality

In the context of interactive service delivery, service quality (SQ) is defined as the customer's viewpoint and overall subjective assessment of the service (Dabholkar et al., 2000). According to Shahid et al. (2018), a company's assessment of the quality of service is based on how closely it follows the original plan. It's crucial to remember that physical and online services are very different from one another. Only when a service provider is offline can customers interact with them. Customers are likely to interact with both the website and the service providers in an e-commerce setting. Ashfaq et al. (2020) suggested that satisfaction of customers, a measure of behavioural intention, and chatbot SQ are positively correlated.

Hypothesis 5 (H5): SQ positively affects the PU of chatbot users.

Hypothesis 6 (H6): SQ positively affects the PE of chatbot users.

Perceived usefulness

Using the definition provided by Davis (1989), PU is the extent to which a person thinks that using a certain approach will improve their odds of success on the job. The notion gained popularity because to the TAM, which considers a person's attitudes towards the adoption of a technology in relation to PU and PEOU (Davis, 1989). However, research has shown that, when comparing the effects of PU and PEOU in both before and after acceptance of a technology, usefulness continues to have an impact on both stages, but ease of use affected attitude inconsistently, which then appears to diminish and lose significance in the post-acceptance stage (Davis, 1989). Customers' demands for ease of use tend to disappear once they get used to the technology, and are replaced by more perceptive opinions about how well the innovation improves one's performance at work (i.e., PU). Because of this discovery, Bhattacherjee's (2001) proposed that customers' satisfaction and chatbot continuance are primarily based on PU, such as using chatbots, is advantageous for supporting his or her activities and aids in efficiently performing some specific tasks. According to the expectation-confirmation method, the main foundation of CI in this study is PU. Whether or not compared to human service interaction, several studies have recognised PU as a critical component in defining the chatbot user experience (McLean et al., 2020). Customers would be happy to use a chatbot if it provided more value than the price they paid, according to social exchange theory (Emerson, 1976). On the other hand, a user may believe that the contact was less valuable than it was if they do not receive assistance from the chatbot.

Hypothesis 7 (H7): PU positively affects the CI of chatbot users.

Perceived enjoyment

The underlying significance of technology adoption behaviour is also determined by PE (Davis, 1989). PE, often known as intrinsic motivation, is recognised as a critical component of end-user adoption in an expanded version of TAM by Venkatesh and Bala (2008). Enjoyment has been described as the extent to which individuals feel that using a computer is naturally pleasurable and satisfying.

PE has been shown to have a beneficial impact on the intention of behavior. Customers may get a positive feeling while interacting with a chatbot, which will raise their level of satisfaction overall. It has been documented in the literature that those consumers who get satisfaction from and consider a technology entertaining throughout their use may have positive effects on both user continuance and intention satisfaction (McLean et al., 2020). Users can occasionally use technologies for pleasure and fun rather than just performance enhancement. Customers are therefore thought to be happier and more inclined to continue with the service in the future when they have a positive and pleasurable experience.

Hypothesis 8 (H8): PE positively affects the CI of chatbot users.

Continuance intention

In information technology, the idea of continuance intention (CI) has gained attention from academics as a crucial field of study that aims to understand consumers' post-adoption attitudes and behaviours. Intention was identified as the ultimate dependent variable in a number of research in consumer behaviour and the information sciences (Zeithaml et al., 1996). According to Jahanmir (2020), CI is the consumers' long-term desire to utilise a technology on a regular basis. Without users who expect to reap the advantages of continuing to use a technology, it would be ineffectual and unprofitable. Numerous information system and digital technology environments, such as online banking, technologies such as social recommendation systems, virtual worlds, wearables, and massive open online courses, mobile government, and more, have been the focus of study with the continuance intention (Wang et al., 2020). Consistent with previous research, this study chose to use chatbot CI as the dependent construct.

The moderating role of interactivity

Interactivity (INT) has emerged as a defining characteristic of online service systems, particularly in transforming static content into dynamic, two-way interactions that mimic real-world conversations (Fan et al., 2020). As online shopping increasingly replaces face-to-face transactions, INT enables users to customize content, receive real-time feedback, and control the flow of information, making the digital experience more engaging (Fiore et al., 2005). In this study, INT is defined as the customer's ability to adjust the mediated environment's structure and content in real time (Fiore et al., 2005). Through features like personalized responses, dynamic visuals, and engaging dialogue flows, interactive chatbots can enhance user engagement by making information feel more accessible and actionable (Baek et al., 2019).

While earlier research generally views INT as a direct predictor of user perceptions, this study views it as a moderator, boosting or decreasing the impacts of IQ on PU and PE. The positive effect of IQ on PU is particularly great when INT is high because users may actively engage with and navigate the content, thereby making it seem more relevant and helpful. Users are more likely to like IQ offered by a highly interactive chatbot owing to its engaging, responsive, and personalised character (Baek et al., 2019).

Hypothesis 9 (H9): INT positively moderates the relationship between IQ and PU, such that the relationship is stronger when INT is high.

Hypothesis 10 (H10): INT positively moderates the relationship between SQ and PE, such that the relationship is stronger when INT is high.

Conceptual Framework of the Research

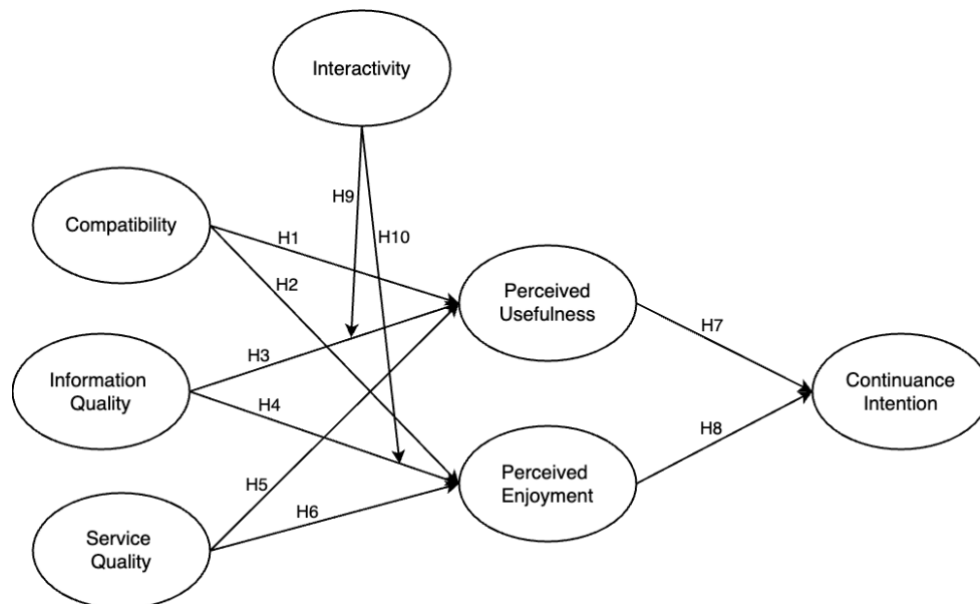To test its hypotheses, the research suggests a conceptual framework:

Figure 1: Conceptual framework

Research and Methodology

Participants and Data Collection

This research is quantitative in nature, and the method of sampling will involve non-probability sampling with snowball and convenience sampling techniques. The population is consumers who have used AI chatbots. To gather information from the research sample, a Google Form is used to generate a questionnaire. The final design is modified through a pilot test. An overview of chatbots will be provided at the start of the survey, along with examples. The survey includes a filtering question to find out how respondents have interacted with chatbots. Individuals without any prior experience with chatbots are not eligible to take part in the research.

Measurements

The measures in this study are adopted from previous literature. INT and COM are measured by scales from Hari et al. (2022). IQ, SQ, PU, and PE scales are adopted from Ashfaq et al. (2020). CI items are adopted from Bhattacherjee (2001).

Data Analysis

The study conducted SEM-PLS (Structural Equation Modeling-Partial Least Square) through the Smart PLS 4.0 software application.

Findings and Discussion

Validity Analysis

Empirical data were collected from 756 respondents. The data reveals that the largest percentage of respondents identified as male (68.5%), followed by female respondents (29%), and those who chose not to disclose their gender (1.5%). Geographically, the majority of the participants (95%) were from Asia. Age-wise, the data shows most of the responders (75.4%) fell into the 18-25 age group, while 15.1% were below 18, 5.9% were between 36-45, 1.7% were between 26-35, 1.3% were 56 and above, and 0.6% were between 46-55. When it comes to education level, 44.1% of respondents reported having a bachelor's degree, while 41.6% had a high school diploma or equivalent. Regarding marital status, the majority of respondents (89.1%) reported being single.

Validity of the items for all constructs can be identified from the loading factor value (> 0.7) and the AVE value (> 0.5) to demonstrate convergent validity. The loading factor values for all items are above 0.7, and the AVE values for all scales are above 0.5. Therefore, all items and variables are considered valid and have good convergent validity.

Table 1: Validity test

Variable	Items	Outer loadings (standardized)
COM	COM1	0.883
	COM2	0.919
	COM3	0.895
CI	CI1	0.885
	CI2	0.893
	CI3	0.883
INT	INT1	0.862
	INT2	0.918
	INT3	0.924
	INT4	0.892
IQ	IQ1	0.882
	IQ2	0.903
	IQ3	0.898
	IQ4	0.917
	IQ5	0.903
	IQ6	0.883
	IQ7	0.895
PE	PE1	0.902
	PE2	0.928
	PE3	0.929
	PE4	0.887
	PE5	0.836
PU	PU1	0.899
	PU2	0.912
	PU3	0.917
	PU4	0.894
SQ	SQ1	0.887
	SQ2	0.911
	SQ3	0.885
	SQ4	0.903
	SQ5	0.884
	SQ6	0.882

Reliability Analysis

Reliability of the measures can be demonstrated from the composite reliability value with a value > 0.7 and Cronbach's alpha with a value > 0.7. All scales in this study are considered highly reliable with all Cronbach's alpha values > 0.9. This suggests that the questionnaire used in the study is highly reliable and possesses excellent internal consistency. (See table 2)

Table 2: Reliability test

	Cronbach's alpha (standardized)	Cronbach's alpha (unstandardized)	Composite reliability (rho_c)	Average variance extracted (AVE)
CI	0.917	0.917	0.917	0.787
COM	0.926	0.925	0.927	0.809
INT	0.944	0.943	0.944	0.809
IQ	0.967	0.966	0.967	0.805
PE	0.954	0.953	0.953	0.805
PU	0.947	0.947	0.948	0.820
SQ	0.959	0.959	0.959	0.796

Hypothesis Result

This hypothesis testing is conducted through bootstrapping. The direct effect and indirect effect tests aim to answer the research hypothesis with significant criteria being the t-statistics value > t-table (1,960) or the p-value < 0.05. The hypothesis result can be seen in Table 3.

Table 3: Hypothesis testing results

Hypothesis		Original sample (O)	T statistics	P values	Result
H1	COM -> PE	0.189	2.823	0.005	Supported
H2	COM -> PU	0.101	1.710	0.087	Not supported
H3	IQ -> PE	0.206	2.316	0.021	Supported
H4	IQ -> PU	0.223	2.965	0.003	Supported
H5	PE -> CI	0.569	12.535	0.000	Supported
H6	PU -> CI	0.351	7.693	0.000	Supported
H7	SQ -> PE	0.426	5.157	0.000	Supported
H8	SQ -> PU	0.522	6.828	0.000	Supported
H9	INT x IQ -> PE	0.220	3.494	0.000	Supported
H10	INT x IQ -> PU	0.186	3.583	0.000	Supported

Based on the analysis in Table 3, several significant relationships were identified. Hypothesis 1, 3, 4, 5, 6, 7, 8, 9, 10 are supported, while hypothesis 2 is not supported. COM has a significant positive effect on PE (t = 2.823, p = 0.005), but its influence on PU is not significant (t = 1.710, p = 0.087). INT shows a significant positive effect on PU (t = 2.247, p = 0.025), but its effect on PE is not supported (t = 1.5q69, p = 0.117). Both IQ and SQ significantly influence PE (t = 2.316, p = 0.021 and t = 5.157, p = 0.000, respectively) as well as PU (t = 2.965, p = 0.003 and t = 6.828, p = 0.000, respectively). In addition, PE (t = 12.535, p = 0.000) and PU (t = 7.693, p = 0.000) both have a significant positive effect on CI. The interaction analysis shows that the combination of INT and SQ has a significant but negative effect on both PE (t = 2.205, p = 0.028) and PU (t = 3.356, p = 0.001). On the other hand, the interaction between INT and IQ shows a significant positive effect on PE (t = 3.494, p = 0.000) and PU (t = 3.583, p = 0.000).

Discussion

The effect of compatibility on perceived usefulness and perceived enjoyment

The results show that COM has a significant positive effect on PE but does not have a significant effect on PU. Previous studies in various technology adoption contexts support the positive role of COM in enhancing user enjoyment. For example, research on smart classroom adoption found that COM improved users' enjoyment by making the technology feel more aligned with their needs and experiences (Setälä et al., 2025). Similarly, COM was shown to enhance PE in both educational and professional technology use cases (Rad et al., 2023).

However, its lack of influence on PU may be explained by the nature of the user group, which means the outcome may not be universally applicable across all groups; rather, it could reflect characteristics specific to the sample population. Since the study was conducted on younger users who are highly familiar with technology, they may view COM as a basic expectation rather than a feature that enhances functional value. For this demographic, PU might depend more on task-specific features or performance than on general COM. This explanation is consistent with Setälä et al. (2025), who noted that while COM affects PE, its effect on PU may be less pronounced or dependent on other factors.

The effect of information quality on perceived usefulness and perceived enjoyment

According to the findings, the PU of chatbot users is significantly and positively impacted by IQ. For chatbots, which are typically designed to help users locate relevant information and provide advice, instructions, and suggestions, the information must be well-structured, easily comprehensible, trustworthy, and helpful. Users perceive the technology as useful when the chatbot provides timely and accurate information.

This result is supported by Veeramootoo et al. (2018), who found that IQ predicts PU in virtual community contexts. Similarly, Chen and Tsai (2019) found that IQ positively affects PU in the context of customized, location-based mobile applications. Moreover, PE is also positively associated with IQ. Merkouris et al. (2022) found that when there are no barriers or challenges in the information-seeking process, users are more likely to enjoy the interaction.

The effect of service quality on perceived usefulness and perceived enjoyment

PU is also found to be positively and significantly impacted by SQ. This finding contrasts with Zhou (2011), who did not observe a direct relationship between SQ and PU in mobile website adoption. However, it aligns with prior research showing that SQ plays an important role in shaping user experience with technology (Ashfaq et al., 2020). \

PE is likewise positively affected by SQ. Chatbots offering high-quality service can enhance users' emotional experience and enjoyment. Shahid et al. (2018) reported a positive relationship between customer satisfaction and SQ in self-service technologies. Ashfaq et al. (2020) also confirmed that high SQ improves customer impressions and overall experience with chatbots.

The effect of perceived usefulness and perceived enjoyment on continuance intention of chatbot users

PU has a significant positive effect on users' CI, as predicted. This demonstrates that users are more likely to continue using a technology they perceive as helpful. If users believe that chatbots help them achieve their goals or solve problems efficiently, they are more inclined to keep using them. These results align with McLean et al. (2020) in the context of web-based services. Additionally, PE also positively influences CI. Users are more likely to continue using chatbots that are engaging and enjoyable to interact with.

The moderating role of interactivity

The results show that chatbot INT moderates the relationship between IQ and both PE and PU. This means that while high-quality information is important, its impact on user experience depends on how interactive the chatbot is. Prior research on mobile instant messengers supports this, showing that INT strengthens the effect of information-related features on PU (Fan et al., 2020). Similarly, in VR shopping contexts, INT has been found to enhance users' perception of usefulness and enjoyment when the system provides vivid and rich information (Baek et al., 2019). These findings suggest that interactive features help users better engage with and appreciate the information provided, making it feel more useful and enjoyable.

Conclusion

This study provides a comprehensive understanding of the variables affecting users' experiences when using chatbots by examining the determinants of PE, PU, and CI. The results improve our comprehension of the TAM framework and its relevance to chatbot technology by illuminating the elements that affect users' perceived values. By highlighting COM, IQ, and SQ as critical determinants of PU and PE, this study expands on the TAM model. The study also contributes to the current growing literature of AI chatbots by identifying INT as a moderator of the relationship between IQ and both PE and PU.

Practically, managers of businesses may concentrate on making sure that their chatbots give high-quality information, satisfy customer demands and preferences, and create positive service experiences, while making sure their AI chatbot is interactive for the users. Managers may invest resources to enhance CI of customer experience by understanding the determinants of chatbots.

The following are a few recommendations for further research on AI chatbots:

i. Future studies can expand the understanding of chatbot usage by focusing on different chatbot applications beyond the context used in this study, or by exploring chatbots designed for specific industries, such as healthcare or finance, where user needs and expectations might differ.

ii. Future research could also apply new theoretical frameworks or adopt alternative research models, allowing the field to grow through different academic perspectives and approaches.

iii. Conducting longitudinal studies or direct surveys over an extended period could provide more precise comprehension of how user attitudes and behaviours towards chatbots evolve over time.

iv. Researchers can also examine emerging concerns such as chatbot ethics, data privacy, and the psychological implications of excessive personalization.

v. Future studies can compare chatbot adoption and user responses across cultures to understand how regional norms, language, and trust levels influence engagement.

References

Ashfaq, M., Yun, J., Yu, S., & Loureiro, S. M. C. (2020). I, Chatbot: Modeling the determinants of users' satisfaction and continuance intention of AI-powered service agents. *Telematics and Informatics*, 54, 101473.

Baek, H., Kim, S., & Lee, S. (2019). Effects of interactivity and usage mode on user experience in chatbot interface. *Journal of the HCI Society of Korea, 14(1)*, 35-43.

Bharatkumar, Sukhiyaji. (2024). Digital Transformation In Business - The Impact Of AI In Enhancing Customer Experience. *IOSR Journal of Business and Management. 26.* 53-58. 10.9790/487X-2610145358.

Bhattacherjee, A. (2001). An empirical analysis of the antecedents of electronic commerce service continuance. *Decision support systems, 32*(2), 201-214.

Chen, C. C., & Tsai, J. L. (2019). Determinants of behavioral intention to use the Personalized Location-based Mobile Tourism Application: An empirical study by integrating TAM with ISSM. *Future Generation Computer Systems, 96,* 628-638.

Dabholkar, P. A., Shepherd, C. D., & Thorpe, D. I. (2000). A comprehensive framework for service quality: an investigation of critical conceptual and measurement issues through a longitudinal study. *Journal of retailing, 76*(2), 139-173.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, 319-340.

Emerson, R.M. (1976). Social exchange theory. *Annual Review of Sociology, Vol. 2 No. 1, pp. 335-362.*

Fiore, A. M., Kim, J., & Lee, H. H. (2005). Effect of image interactivity technology on consumer responses toward the online retailer. *Journal of Interactive Marketing, 19*(3), 38-53.

Gartner (2018). How to Manage Customer Service Technology Innovation. URL: https://www.gartner.com/smarterwithgartner/27297-2/ (visited on 10/03/2021).

Hari, H., Iyer, R., & Sampat, B. (2022). Customer brand engagement through chatbots on bank websites–Examining the antecedents and consequences. *International Journal of Human–Computer Interaction, 38*(13), 1212-1227.

Jahanmir, S. F., Silva, G. M., Gomes, P. J., & Gonçalves, H. M. (2020). Determinants of users' continuance intention toward digital innovations: are late adopters different? *Journal of Business Research, 115*, 225-233.

Lee, J., Hwang, C., & Kwon, D. (2015). On the effect of perceived security, perceived privacy, perceived enjoyment, perceived interactivity on continual usage intention through perceived usefulness in mobile instant messenger for business. *Journal of Korea Society of Digital Industry and Information Management*, *11*(3), 159-177.

Letheren, K., Russell-Bennett, R., & Whittaker, L. (2020). Black, white or grey magic? Our future with artificial intelligence. *Journal of Marketing Management*.

Lu, L., Cai, R., & Gursoy, D. (2019). Developing and validating a service robot integration willingness scale. *International Journal of Hospitality Management, 80*, 36-51.

McLean, G., Osei-Frimpong, K., Al-Nabhani, K., & Marriott, H. (2020). Examining consumer attitudes towards retailers' m-commerce mobile applications–An initial adoption vs. continuous use perspective. *Journal of Business Research, 106*, 139-157.

Merkouris, S. S., Loram, G., Abdelrazek, M., Rodda, S. N., Ibrahim, A., Bonti, A., & Dowling, N. A. (2022). Improving the user experience of a gambling support and education website using a chatbot. *Universal Access in the Information Society*, 1-13.

Przegalinska, A., Ciechanowski, L., Stroz, A., Gloor, P., & Mazurek, G. (2019). In bot we trust: A new methodology of chatbot performance measures. *Business Horizons, 62*(6), 785-797.

Rad, D., Egerău, A., Roman, A., Dughi, T., Kelemen, G., Balaș, E., ... & Kiss, C. (2023). On the technology acceptance behavior of Romanian preschool teachers. *Behavioral Sciences, 13*(2), 133.

Rogers, E. M. (1995). Diffusion of innovations, edition of the Free Press. *The fourth.*

Setälä, M., Heilala, V., Sikström, P., & Kärkkäinen, T. (2025). The Use of Generative Artificial Intelligence for Upper Secondary Mathematics Education Through the Lens of Technology Acceptance. *arXiv preprint arXiv:2501.14779.*

Setia, P., Setia, P., Venkatesh, V., & Joglekar, S. (2013). Leveraging digital technologies: How information quality leads to localized capabilities and customer service performance. *MIS quarterly, 565-590.*

Shahid Iqbal, M., Ul Hassan, M., & Habibah, U. (2018). Impact of self-service technology (SST) service quality on customer loyalty and behavioral intention: The mediating role of customer satisfaction. *Cogent Business & Management, 5(1), 1.*

Tornatzky, L. G., & Klein, K. J. (1982). Innovation characteristics and innovation adoption-implementation: A meta-analysis of findings. *IEEE Transactions on engineering management,* (1), 28-45.

Veeramootoo, N., Nunkoo, R., & Dwivedi, Y. K. (2018). What determines success of an e-government service? Validation of an integrative model of e-filing continuance usage. *Government information quarterly, 35*(2), 161-174.

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision sciences, 39*(2), 273-315.

Wang, C., Teo, T. S., & Liu, L. (2020). Perceived value and continuance intention in mobile government service in China. *Telematics and Informatics, 48*, 101348.

Zeithaml, V. A., Berry, L. L., & Parasuraman, A. (1996). The behavioral consequences of service quality. *Journal of marketing, 60*(2), 31-46.

Zhou, T. (2011). Examining the critical success factors of mobile website adoption. Online information review, 35(4), 636-652.